Identification of Cognitive Workload using EEG Signal Processing

SHORT SYNOPSIS

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Certificate

I hereby declare that the short synopsis " Identification of Cognitive Workload using EEG Signal Processing" being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in ECE Department under faculty of Engineering & Technology of Manav Rachna International Institute of Research & Studies, Faridabad during the academic year 2016.

It is a bonafide record of original work carried out under the supervision of Dr. Dipali Bansal & Dr. Rashima Mahajan and has not been submitted in full or part to any other university or institute for degree or diploma. Further, it is certified that short synopsis is plagiarism free and proof has been submitted.

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ABSTRACT

Electroencephalography (EEG) is a reliable biomedical signal to efficiently evaluate the cognitive state of the brain. EEG signals are helpful in better analysis of cognitive process. EEG provides information about the brain but research in the field of classification and evaluation of EEG signals is still lacking. Enhanced EEG acquisition systems, robust signal processing algorithms and classification rules are required to observe delicate changes in brain waves when subjected to cognitive tasks. The analysis of EEG signals for cognitive workload identification with higher accuracy and reduced complexity is required. A catalogue of EEG data is required to be prepared to analyze brain templates indicating changes due to the cognitive workload. The primary aim will be the analysis of digital filter structures to eliminate noise in EEG signals by overcoming their limitations such as lesser signal to noise ratio, higher mean square error etc. An efficient filter structure possessing high PSNR (peak signal to noise ratio) value while removing EEG signal artifacts shall be proposed. An extensive cognitive workload specific EEG signal database shall be constructed. An effort shall be attempted to develop more accurate algorithm with reduced complexity to identify the effect of various cognitive tasks on the human brain. An efficient feature extraction algorithm in Matlab shall be developed to identify cognitive state & the robustness of the algorithm developed shall be evaluated.

Key words: Electroencephalography, Cognitive, Matlab, Digital Filter, Artifact, Workload

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1. Introduction

The electroencephalogram (EEG) is a multi-channel indicator of brain activity which might imitate brain states associated with the cerebral condition of a human being (Raduntz et al., 2015; Khatter, 2017). EEG is a broadly used methodology for examining the functioning of the human brain. The amplitude of an EEG signal varies in the range 10 to 100 microvolt and frequency varies from 1 to 100Hz. A brain-based ability essential to carry out each task which varies from the modest to the intense complex is cognitive ability. Electroencephalography is a consistent biomedical signal that offers an approximate estimation of individual psychological feature ability. Cognitive involves the potential to get information which might merely be tested. The cognition is totally different from emotional, social, artistic development and talent. In cognitive abilities emphasizes isn't on actual information, it's the priority with the way to learn, recall, listen and solve the matter. Cognitive science learns regarding the surroundings, the chores, and therefore the roles of knowledge. Cognitive science is an associate emerging field that deals with thinking, human perception and learning. The study of the mind through neurobiology, psychology, engineering science, social science, linguistics, and philosophy is cognitive science. Cognitive science is thinking about how we think. To grasp the mind it's significant to understand how the brain works. The neuroscience offers abundant ways to seem at the brain in several strategies (Khatter, Bansal and Mahajan, 2017). Recently, analysis goes in the direction of assessing mental states of human – like psychological feature (cognitive workload) and task engagement (Chandra et al., 2015). Many researches explored encephalogram mostly cataloguing and assessment of the person memory load (Hefron et al.,2018; Zarjam et al.,2015 ; Marinescu et al.,2016; Spüler et al.,2016; Gentili et al., 2014; Taya et al., 2015). Several strategies are employed by researchers for estimating psychological feature workloads like distinguishing multiple biomarkers, data processing and machine learning; attention training that reduces the time complexity and their dimension representations (Khatter, Bansal and Mahajan, 2017).

A main complexity is that the contamination of graphical record signal varied by physiological and non-physiological artifacts like movement of patient head, blinking of an eye , rotation of eyeball, sweating, activity of muscle and the heartbeat, external faults like electrode failure, power supply and ventilation (Raduntz et al., 2015;Khatter, 2017). Artifacts are the unwanted noise or definite disruption created throughout the recording of brain signals. The eradication of artifact in encephalogram is crucial. The existence of electrical artifacts created by the eye blinks and an eye

movement's contamination produce a signal referred as Electrooculogram (Mosquera and Vazquez, 2009). The frequency range of ocular artifacts is same as encephalogram signals so proficient algorithms are needed to eradicate the artifacts. (Bhuvaneswari and Kumar, 2012; Khatter, Bansal and Mahajan, 2017).Human performance is suffering from the mental workload (Marinescu et al., 2016). To remove the autonomous components from the preliminary EEG signal, the spatially-constrained ICA and wavelet denoising method are employed to extract the activity of the brain (Geetha and Geethalakshmi, 2012). The Otsu thresholding is an improved technique for the elimination of artifacts than other existing ways.

A digital filter is employed to eradicate noise within the EEG signal (Podder et al., 2014). Digital filters are divided into two types - Finite Impulse Response (FIR) filter and Infinite Impulse Response (IIR) filter (Eka et al., 2016; Podder, 2014; Proakis and Manolakis, 2007). In the FIR system, the impulse response is of limited duration whereas the IIR system has unlimited duration. While realization, no feedback is required in FIR filter (Proakis and Manolakis, 2007) because of that, the construction of FIR filter is easier than IIR filter (Proakis and Manolakis, 2007; Chandra and Chattopadhyay, 2016). The IIR and FIR filter are chosen according to the requirements and specifications of frequency response then an appropriate method is applied like Fourier series method ,Frequency sampling method or Window method, through which the FIR filter will be obtained (Proakis and Manolakis, 2007; Mehboob et al.,2009) . Out of these methods, window techniques are typically used (Zahoor, Naseem and Meng, 2017). This short synopsis presents an overview of construction of an EEG database, signal processing to identify efficient digital filter structure to eliminate the artifacts and feature extraction to identify the effects of cognitive levels on the human brain. An extensive literature review highlights the gaps in literature. After a description of the research topic and problem statement formulation, objectives of the present research work are defined explicitly. In the last, structure and flow of the present work with methodology, the proposed time required to complete this research along with the expected outcome of the proposed research is described.

2. Literature Review

A lot of literature analysis on the physiological signal processing as well as its current applications, has been done. This section includes the most recent techniques implemented by a researchers for artifact removal and followed by the methods of feature extraction used to classify the effects of cognitive levels on human brain i.e., EEG.

Artifact Removal Techniques for EEG

In the health library of Johns Hopkins medication, it's illustrated that there are a number of abnormal electrical impulses in a brain throughout a seizure (Siuly, Li and Zhang, 2016) and whenever there's epilepsy, seizure action can appear as speedily growing spiking waves within the EEG (Holler and Trinka,2015). There are several challenges in getting EEG during movement as during motion it was absolutely tough to get clean cerebral data. However, by applying computational strategies, difficulties are often handled (Thompson et al., 2008; Bell and Cuevas, 2012) There are several effective methods to understand cortical processes. Alternative challenges are EEG has a superb temporal resolution, but deprived spatial resolution (Bell and Cuevas, 2012).The skull act as a low-pass filter that pretends like an electrical movement of the brain over the scalp. At the scalp, recorded potentials are produced by several alliances of cortical and then sub cortical generators that extend across a fairly wide region (Pizzagalli, 2007). An electrode at the scalp is probably distinguishing electrical activity that generates from non-local clusters of neuron that's the reason a more robust way to discuss EEG activity is at some precise electrode location rather than from a specified area of the brain (Reynolds and Richards, 2009).

The eradication of artifact in EEG is crucial and many techniques were used by researchers for eliminating artifacts. The stationary and discrete wavelet transforms (SWT &DWT) is suitable in the single channel EEG for data artifact removal and to realize ambulatory real-time EEG systems (Khatun et al. 2015). The artifact effects are eradicates or lessen by another technique also like operative artifact removal technique (Goh et al., 2017). The characterization of spatiotemporal-frequency influence artifacts and proposed two resolutions. A projected resolution gives an enhanced spatiotemporal-frequency recital. The proposed ARTs achieve an improved SNR and improved clutter to signal ratio score in produced data. These techniques have a lesser amount of restrictive previous supposition on artifact features. A manifold signal-processing tools with template matching technique was evaluated and verified for real EEG signals and consequences illustrates this system

has superior competences in routine EEG studies (Eldeen, Farag and Allah, 2017). A proposed framework mixes ICA, regression and high-order data for classification & elimination of artifacts from EEG data (Mannan, Jeong and Kamran, 2016). The simulated, experimental and standard EEG signals are used to evaluate the utility of proposed technique. The results are evaluated with other accessible methods independent components analysis, wavelet independent components analysis, regression analysis and regression independent components analysis and the analysis reveal that this technique eradicate ocular artifacts and save the movement of neuronal linked with input signals. Another technique is proposed which is carried out for every EEG channel locations and it was independent of number of EEG channels used. The visual evaluation of 2D scalp map projections of the independent components (known as topoplots), are proposed with a classification evaluation by the use of mixing matrix columns (Raduntz et al., 2015). This technique is used as universal as this technique is independent of the number of EEG channel used. Also this technique can be applied online on diverse experiments and subjects because it is not restricted to the artifacts type. In manual classification, there is the possibility of dissimilarity in SNRs with experts and with machine de-noising (Winkler, Haufe and Tangermann, 2011). A merging independent components analysis and auto-regressive exogenous independent components analysis (ICA-ARX) technique is applied to eradicate ocular artifact (Wang et al., 2014). A negative consequence of ICA is lessen with the ARX. The limitation in this research is that only ARX variation for fast ICA is taking into consideration, without investigating the recital when different ICA are combined with ARX. Another technique to eliminate the ocular artifact and create a reference signal is discrete wavelet transform along with adaptive method. The ocular artifacts are robustly cancelled by adaptive noise canceller. The ocular artifacts are significantly affected in the low- frequency zone and to identify this zone discrete wavelet transform is employed as a filter bank. The thresholding method with the appropriate threshold value is also used to eliminate noise in the EEG signal. The proposed method is the combination of two different methods where suitable selection of forgetting factor proposed the excellent consequence to eradicate ocular artifact and obtaining a true EEG (Sanaja & Patel, 2015).

An independent component analysis (ICA) and recursive least squares (RLS) are used to eradicate artifacts due to the movement of eyes (Mosquera and Vazquez, 2009). By placing separate electrodes near the eyes, vertical and horizontal movements of eyes are recorded and reference signal is extracted. Every reference input is envisaged into the independent component analysis field and interference is evaluated by the recursive least squares algorithm and subsequently in the domain of independent component analysis, the evaluated interference is removed from the components of EEG.

The evaluation of a real signal is much complex than a simulated signal because real EEG signals are nonstationary in nature (Valipour, Kulkarni and Shaligram, 2015). An evolutionary stone's blind source separation algorithm automatically remove the heartbeat and ocular artifacts without the use of notch filter which is demonstrated on the super-Gaussian and the sub-Gaussian signal from brain (Abdullah et al., 2014). EEG blended automatically and simultaneously and compared with various kinds of blind source separation algorithms and results reveals that evolutionary stone's blind source separation algorithms are proficient to eliminate other types of artifacts also. A data-driven surrogate based artifact removal (SuBAR) is an auspicious technique for portable environments to classify and remove ocular and muscular artifacts from single-channel electroencephalography. This technique is competent when slight as well as severe artifacts are present and provides improved efficiency than other type of existing single-channel EEG denoising techniques. This technique also provides a minimum distortion of the signals. This technique is not capable to detect and remove long and tenacious muscular artifacts because the spectrum of impure EEG is same as of a stationary process (Chavez et al., 2018; Mannan, Jeong and Kamran, 2016).

The blending of discrete wavelet transform, independent component analysis and wavelet-independent component analysis was employed to remove components of artifact. A priori information of artifact is obtained online and in wavelet independent component analysis (WICA) priori information of artifacts is provided with the data having artifact. The artifacts are recognized and removed by cataloging the grouping of the noticeable priori information of artifact and wavelet independent component. A teeth gritting, eye blinking and rolling and was used for a priori electromyography and electrooculography information of artifacts. WICA enhances the recital of ICA because the data is moved into new space where redundancy is more and the artifact features are completely used. But only few number of WICs is present, a huge number of artifact removal components leads to the additional removal of artifacts and it works only on WICA and can't found whether it works for other techniques of ICA and in diverse situations or not(Zhang et al., 2015).. A digital filter is also used to eliminate the noise present in the EEG signal (Podder et al., 2014).The digital filters are of two types: Infinite Impulse Response (IIR) filter and Finite Impulse Response (FIR) filter (Diana et al.,2016; Proakis and Manolakis, 2007). The IIR and FIR filter is chosen as per the requirement and specifications of frequency response and subsequently a appropriate method is applied like frequency sampling method, fourier series method or window method (Mehboob et al., 2009). There is a possibility to loss data in automatic identification of artifacts whereas in manual artifact identification more time is required (Bhuvaneswari and Kumar, 2012). A variety of methods

are examined for the eradication of artifacts from EEG signals with their shortcomings and study reveals that a competent method with higher accuracy is required for the removal of an artifact. Considering the above facts an effort shall be attempted to develop an efficient filter structure to eliminate artifacts.

Feature Extraction Techniques for EEG

This section presents a review of emerging research in the field of different cognitive levels on human brain. An artificial neural network relates the competence of three techniques for feature extraction i.e. discrete wavelet transforms (DWT), power spectral density (PSD), and empirical mode decomposition (EMD) in the automatic cataloging of sleep phases (Prucnal and Polak, 2017). The competence of PSD is superior to EMD and DWT in this precise cataloging problem. By uniting selected estimation and detailed coefficients, there is a probability of removing the distinctive frequency sub-bands from DWT and that should be tested. With the use of Hilbert transform, EMD coefficients will be tested. Analyzing additional classification approaches like the support vector machine and decision trees will give improved cataloging accuracy than achieved in this study. The cluster analysis technique of feature extraction has the benefit that it does not determine by well-defined class of learning and training (Huang and Xiao, 2011).

Researchers **(**Azlan and Low, 2014) reviewed various techniques for schizophrenia on signal analysis for feature extraction of EEG signal i.e. Hilbert-Huang transform, Independent Component Analysis, Principal Component Analysis, and Local Discriminant Bases. Local Discriminant Bases is an alternative feature extraction method for EEG signal in examining schizophrenia. More exploration is required in extracting the features of EEG signal in schizophrenia. A Field Programmable Gates Array (FPGA) strategy is used for feature extraction of real time EEG signals which employs for implementation of Short-time Fourier Transform and removes 20 feature components of frequency for cataloging (Zhang, 2017). With the use of Xilinx System Generator, a model is designed and applied on a Xilinx Zedboard with clock rate of 50MHz and the model is capable of 128-channel EEG signals feature removal at sample rate of 250 Hz and is capable for BCI applications. The limitations in their study are that the design model is not evaluated on widely existing EEG data sets to extract the features & to train artificial neural network for EEG signals. Also, the hardware of the designed model is cumbersome for the implementation of huge number of features.

The classifier based on neural network analysis classifier was used to identify epileptic seizure movement from surroundings EEGs (Chandani and Kumar, 2017). DWT signal were reprocessed, decaying until 5th level of decaying tree and for cataloging of signals, different features (standard deviation, mean, median, kurtosis, skewness and entropy) were computed. The results indicates that the cataloging precision of almost 100% in recognition of irregular signal from regular EEG signals with less computation time of NNA classifier. A low-power SoC perform acquisition and feature extraction of EEG which is essential for incessant detection of seizure onset in patients of epilepsy (Verma, et al., 2010). The SoC combine an instrumentation amplifier, digital processor and ADC. It is significant to utilize targeted analog processing to keep away from the restrictions forced by environment, electrode and physiological disturbances. The offered SoC achieved acquisition of EEG, digitization, and feature vector removal. The time frequency distributions (TFD), eigen vector methods (EM), fast fourier transform (FFT), wavelet transform (WT), auto regressive method (ARM) etc methods are used to extract the features of EEG signal (Al-Fahoum and Al-Fraihat, 2014). Out of these five well-known discuss methods; it's very tough to approve any one method according to their capability. Frequency domain technique may not give a high-class recital for a several EEG signal while time-frequency technique may not give comprehensive information on analysis of EEG as given by frequency domain technique. It is critical to create apparent of the signal to evaluate in the application of the technique, whenever the recital of evaluating technique is discussed. The Poincare surface is a noble nonlinear feature which can be employed independently to achieve more than 94% accuracy in the 5-class EEG classification problem (Yang et al., 2017).

A lot of techniques are applied to explore the EEG signal like a unique technique is applied to extend the preceding EEG source imaging work that recognizes natural hand or wrist operations and the result shows that ESI will enhance the BCI (Brain Computer Interface) recital of interpreting intricate right-hand motor imagery jobs(Edelman, Baxter and He, 2016). Using Ultrasound imaging and characterizing various multifaceted hand gestures and authenticating the viability of a muscle - computer interface offers average classification precision is 92% (Akhlaghi et al., 2016). A Brain Machine Interface system is proposed to link EEG with 3 arm movements for directing a robotic arm (Shedeed, Issa and El-sayed, 2013). A BCI is designed to control devices which translate the states of the brain into efficient control signals which can exemplify thoughts, and unspoken words. EPOC headset with 14-channel wireless referential montage can be used for constantly recording of the

brain activities of the human being (Mahajan, Bansal and Singh, 2014; Mahajan and Morshed, 2015).In several clinical and therapy applications, observing is essential because it is difficult for the mentors to investigate the responses of kids having disorders (Mahajan et al., 2013). There are associations amongst central EEG, frontal pole and cognitive recital (Lees, Khushaba and Lal, 2016). By measuring EEG, the person's psychological states can be evaluated with a suitable selection of the channel in case of automated EEG analysis and feature extraction (Islam et al., 2014). Within the same year, a technique is given to recognize the thought patterns supported self-organizing maps (Amarasinghe, Wijayasekara and Manic, 2014). A sensorimotor-rhythm-based noninvasive BCI is competent in providing communication and control capabilities. BCI is incessantly developed still challenges are therein SMR-based noninvasive BCIs – for proficient use of BCI a lengthy training has required (He et al., 2015).

There is a necessity to explore cognitive science and brain computer interface (Chen et al., 2019). As an example, to know the definite difficulties in chess, totally different patterns of cognitive brain mapping of players with distinct levels of experience can be found and analyzed and it had been shown that there are the discriminant variances in the area of cortical brain among beginners and experts graded by their proficiency (Theoto Rocha et al., 2016; Kumar and Kumar, 2016). Cognitive neuroscience of creativity is wide studied with the utilization of non-invasive electrical recordings from the scalp called electroencephalograms and event- related potentials (Srinivasan, 2007). The EEG power spectrum can be used to analyze the cognitive load in Human Computer interface. This methodology has accuracy, they are unbiased and evaluator independent however they require costly equipment, analysis time is high and they require expertise for interpretation. By applying a smart home sensor, clinical scores of people can be predicted with clinical assessment using activity behavior (CAAB) methodology which monitors the everyday activities within the home (Dawadi, Cook and Schmitter-Edgecombe, 2016) . The statistical approach shows that high task load discrimination was mainly attain within the frontal lobe of the brain (Zarjam, Epps and Lovell, 2015). Cognistat screening tools and also the mini-mental state exam (MMSE) was used to review the cognitive performance of participants and vital correlations between MMSE outcomes, the beta activity of EEG (Lees, Khushaba and Lal, 2016).

The above literature findings indicate that an efficient filter structure is required with higher signal to noise ratio and lesser mean square error to eliminate the artifacts from EEG signals.

Along with this an efficient classification of EEG brain patterns under different level of cognitive tasks are required.

2.1 Gaps in Literature

A detailed literature analysis revealed the fact that artifact removal is critical in EEG signals. The use of physiological signals like EEG has gaining a great popularity to analyzing brain patterns under different level of cognitive tasks. Extensive literature has been reviewed to explore that subtle changes in human EEG signals can give an insight into the cognitive workload on a human being. Cognitive workload analysis finds a plethora of applications not only in behavioral analysis but also in the real world environment. Still previous works reveal few limitations like less accuracy; complexity is more; inconsistent findings with lacking substantial conclusion. The highlights of gap in literature are listed below:

- EEG should be captured using the low cost headset which makes EEG as a propitious tool for continuous measurement of the cognitive workload.
- An efficient filter structure with higher signal to noise ratio, cross correlation and lesser mean square error is required for physiological signals.
- Developed BCIs are suffering from conflicting findings. Also, substantial conclusion in the study of various levels on cognitive tasks is lacking. Therefore, enhanced EEG acquisition systems, robust signal processing algorithms and classification rules are required to be developed to observe delicate changes in brain waves when subjected to cognitive tasks.
- Less attention has been paid in developing brain templates indicating changes due to the cognitive workload. A catalogue of EEG data is required to be prepared to develop brain templates indicating changes due to cognitive workload.
- Many researches are working in the domain of the development algorithm to identify the effect of various cognitive levels on the human brain. However, less has been achieved in classifying cognitive states using EEG.

3. Description of Broad Area

Electroencephalography (EEG) is a technique to trace the electrical movement of the brain. The variations in the voltage are measured from EEG .Within the neurons of the brain, there are ionic current which results in voltage variations. People with wounds in their brain, which may be the result of a tumor or stroke, might have abnormally sluggish EEG waves, subject to size and the location of the wound. The EEG also defines the whole electrical movement of the mind like to assess trauma, drug intoxication. In surgical procedures, EEG is used to observe the flow of blood in the brain (Bryn Farnsworth, 2018).

From the normal electrical activities of the brain, a recognizable pattern is made. EEG gives abnormal patterns which show monitor seizure and other disorders. From EEGs, one can identify the causes of several problems like sleep disorders, coma, encephalopathies, brain death, and changes in behavior. It is also employed to assess brain activity in case of head wound or previous to any heart or liver transplantation (Peters, 2018).

The commonly used terms for EEG(Idris et al.,2014):

Delta (0.5-4 Hz): Its amplitude is 20-200μV. This signal occurs during deep sleep and used to detect abnormal brain behaviours & tumours.

Theta (4-8 Hz): Its amplitude is 20-100μV. This signal occurs during the beginning stages of sleep.Generally, this signal is available in children rather than adults.

Alpha (8-13 Hz): Its amplitude is 20-60μV and it is easily produced when eyes are closed & the person is sitting quietly in a relaxed position.

Beta (>13 Hz): Its amplitude is 2-20μV and it is present during mental thought & activity.

An EEG is safe and comfortable and a patient doesn't sense shocks. But having electrodes on the scalp might be a slight tensed as the patient cannot move for the duration of the test. Previously, EEG is also used to investigate for stroke, tumors, and other main brain chaos but when new technologies like high-resolution anatomical imaging method like magnetic

resonance imaging and computed tomography arrive, they are used. In spite of limited spatial resolution, for research and diagnosis EEG is still used to be a valuable tool, mainly when the millisecond-range temporal resolution is required. Evoked potentials (EP) is an EEG technique that involves being an average of EEG motion which are time-locked to the appearance of a stimulus of a selected kind like ocular, somatosensory, or acoustic.

To record actual seizure like ictal recording EEG is continuously recorded with time coordinated video as well as acoustic recording and for this patient have to admit to the sanatorium for few days. Epilepsy is generally completed to differentiate epileptic seizure from various different types of spell. EEG is exploiting to observe the level of an aesthesia or amobarbital effect through the Wada test. It is also employed in severe care part for the functioning of the brain and to observe for non-convulsive status epileptics / non-convulsive seizures.

In research methods, EEG is used to observe minor brain damage in various situations like subarachnoid hemorrhage. The EEG which is directly measured from the cortical surface is called electrocortiogram and EEG taken by depth probes is known as an electrogram. Electroencephalographic interpretation is an entirely non-invasive method which can be applied constantly to patients, adults and kids with nearly no hazard or restriction. Neurosurgeons embed strips, a grid of electrodes; penetrate depth electrodes beneath the dura mater, over a craniotomy. The footage of signals obtained is known as electrocorticography represented as ECoG. This is also described by terms subdural EEG which is represented by sdEEG or intracranial EEG represented by icEEG. Here, the scale of activity to record the signal is different than the brain motion recorded from scalp EEG. In ECoG, the neurosurgeon can simply see low voltage, high-frequency components which are not possible in scalp EEG. After that, there are smaller electrodes which are used to wrap a lighter portion of the brain surface which permit to see even lesser voltage, faster components of brain activity.

EEG and the interrelated investigation of ERPs are exploited broadly in neuroscience, cognitive psychology, cognitive science, neurolinguistics and psycho physiological (Siuly, Li and Zhang, 2016). For clinical use, numerous EEG methods applied in the study to do research are not

uninformed. EEG is widely used in research & treatment in studies like Auditory Processing Disorder (APD), which is research on mental disabilities.

4. Objectives of the Study

4.1 Problem Formulation

Literature review reveals that analysis of EEG for cognitive workload identification with higher accuracy and reduced complexity is required. Analysis of various digital filters is required to eliminate noise in EEG signals by overcoming their limitations such as lesser Signal to Noise Ratio, higher Mean Square Error etc. and to identify the effect of various cognitive tasks on the human brain from acquired EEG signals with higher accuracy and reduced complexity.

4.2 Objectives

1. To study and analyze the effect of various digital filters for artifact removal in EEG signals.

2. To examine the performance of digital filters in real time scenarios.

3. To analyse the database of EEG brain patterns under different level of cognitive tasks.

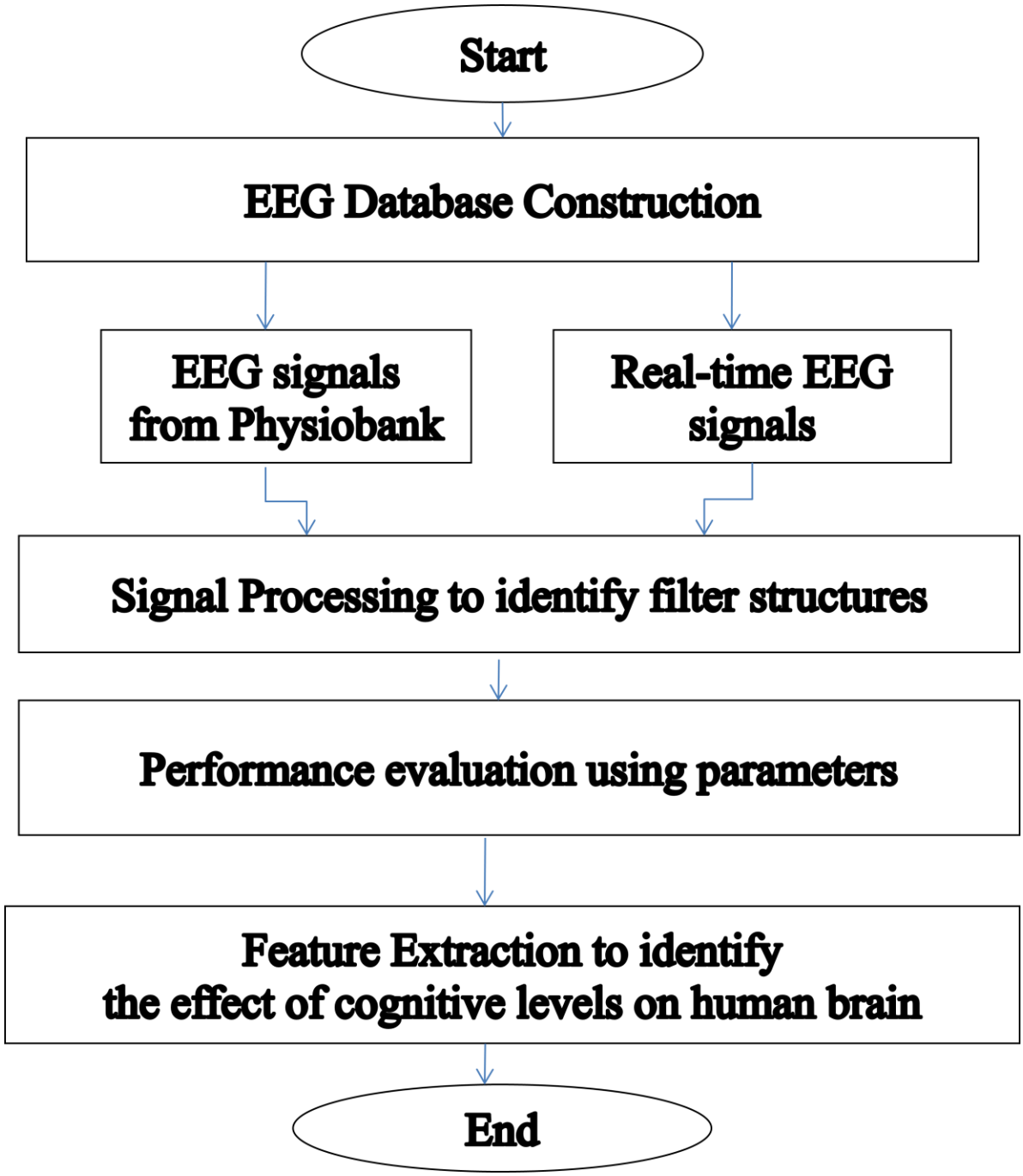
4. To develop efficient signal processing algorithm to identify the effect of various cognitive levels on the human brain.

5. To evaluate the performance of algorithm developed.

5. Methodology to be adopted

Flowchart:-

The loading of EEG signals (signals from database or real time signals) to MATLAB workspace, preprocessing of EEG signals, identification of more efficient filter structure and feature extraction to identify the effects of cognitive levels on human brain can be summed up in the form of an efficient MATLAB algorithm.


Start
EEG Database Construction
EEG signals from Physiobank
Real-time EEG signals
Signal Processing to identify filter structures
Performance evaluation using parameters
Feature Extraction to identify the effect of cognitive levels on human brain
End

Phase1: EEG database collection. EEG signals shall be collected from Physiobank database and real-time signals would also be collected.

Phase2: Signal processing shall be performed to identify the filter structure (IIR and FIR) with high PSNR for removal of artifacts and performance parameters shall be evaluated. Noises will be added to the EEG signal and then IIR and FIR Windowing (Hamming, Hanning, Blackman, Kaiser) filters will be applied to the EEG signal in Matlab and parameters (Mean absolute error, Mean square error, Signal to Noise Ratio, Peak Signal to Noise Ratio, Cross Correlation) shall be calculated to evaluate the performance of filters.

Phase3: The database of EEG brain patterns for different levels of cognitive tasks would be analyzed and signal processing techniques would be developed to identify the effect of various cognitive levels on the human brain.

6. Expected Outcome of the Research:-

1. A digital filter providing high SNR along with a parametric study on artifact removal in EEG signals would be achieved.
2. The performance characteristics of the developed digital filters in real time scenarios would be determined.
3. A signal processing algorithm will be developed for the classification of various cognitive levels on the human brain
4. The various EEG brain patterns under different levels of cognitive tasks would be studied.

7. Proposed Time(Gantt Chart)

Time Frame ⟶	**Jan-Jun 2017**			**July-Dec2017**			**Jan-Jun2018**			**July-Dec2018**			**Jan-Jun2019**			**July-Dec2019**			**Jan-Jun2020**		
Months	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42
Course Work																					
Extensive Literature Search																					
Problem Statement Formulation																					
Publication on Literature Survey																					
Analyze the effect of various digital filters for artifact removal in EEG signals. Examine the performance of digital filters																					
Publication on Digital Filters to eliminate noise in EEG signals																					
Study of EEG brain patterns under different level of cognitive tasks																					
Algorithm development to identify effect of various cognitive levels on human brain																					
Publication on EEG brain patterns & report writing & Submission																					

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